**Ph. D. Registration Research Proposal**

On

# INTELLIGENT ENERGY MANAGEMENT STRATEGIES FOR RENEWABLE ENERGY SOURCES

**For the Doctoral Degree**

In

**Electrical Engineering**

By


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Guide

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# 1 Introduction

In recent years, the significance of renewable energy sources has been increasing. Renewable energy sources are the best alternative for conventional energy sources. Renewable energy sources are abundant in nature, whereas conventional energy sources are exhausting day by day. In this context, a growing interest is now devoted to the development of a smart system in order to suitably manage the electrical energy distribution among different areas optimizing the mix of both renewable and non renewable sources.

To guarantee power supply with the required service reliability at all times in an economical, ecological and resource saving way utilities have to schedule the energy allocation for the next days. Due to worldwide deregulation of the energy market, economic criterion of energy dispatch became more important for the utilities. Therefore an optimization is required even in local service areas and power systems with decentralized feeding.

Especially in electrical system with distributed feeding an intelligent energy management is required to ensure the covering of demand at all times with the required reliability of the supply. The integration of intermittent energy sources such as wind and solar energy in power system brings significant new challenges to the operation and planning of these systems. Traditional dispatch models can no longer guarantee a reliable operation of the system due to high level of uncertainty associated with intermittent power system and new dispatch technique need to be developed. The presence of energy storage system can help to reduce the effect of uncertainty facilitating the integration of variable renewable energy sources if a properly designed energy management system is in place.

As the level of penetration of renewable energy sources within the power system has increased, renewable generation forecasting has become important because of unique characteristics of wind and solar energy and its effect on power system operation. Consequently a large number of researchers are working towards developing good and reliable forecasting models in the recent years and many different approaches have been developed. However, forecasting is a complex task and many exogenous variables interact in an intricate manner. Because of ever increasing complexity of the power system, forecasting these variables with maximum accuracy and minimum computational effort is still an open research issue. Considering these issues in mind, this work will focus on electricity demand and renewable power generation prediction. Different forecasting models will be developed based on time frame, specific application areas which are inadequately researched and forecasting technique.

# 2 Literature Survey

With the emergence of renewable energy sources in power system, forecast of power generation by renewable gained much more importance for proper grid operation. Many different tool and techniques have been developed to handle renewable generation and demand forecasting problem. Considering the need of integrating renewable in power system, Tascikaraoglu [1] has proposed a smart home with various renewable energy sources and storage system control. By using forecasted data and corresponding forecasting error state of charge of the battery, Pascual [2] proposed a strategy which manages to make a better use of the battery resulting in a better grid power profile. In 1998, Yang and Huang have proposed Short Term Load Forecasting (STLF) using time-series based method [3]. Some time series based methods can not yield precise prediction accuracy. Intelligent tools that are able to learn the relation between input and output vectors have been used by many researchers. Feed Forward Artificial Neural Network (FFANN) [4], [5], Fuzzy Neural Networks (FNN) [6], [7], [8], Support Vector Machine (SVM) [9], [10] and Expert System (ES) [11] have been applied in load forecasting area. Hooshmand et al., (2013) showed effectiveness of Adaptive Neural Fuzzy Interference System (ANFIS) based method [12]. Some studies have indicated that wind energy will not cause the significant impacts on reserves if the technique of wind power forecasting can be improved [13]. In 1997, Nogaret et al. have proven that an advavced forecasting technique is required [14]. In reference [15], the authors predicted the hourly average wind speed up to 1 10 hours in advance by using Auto Regressive Moving Average (ARMA) models. A recurrent higher-order neural network (RHONN) model was developed in [16] for wind power forecasting in a wind park which is used to predict wind speed or power in time scales from some seconds to 3 hours. Reference [17]introduces an ANFIS to forecast wind vector 2.5 min ahead, which takes both speed and direction into account. A method based on Artificial Neural Network (ANN) was utilized to predict the average hourly wind speed by Fonte [18]. Reference [19] also utilized ANN to predict day-ahead wind power in Germany. For the training of the ANN, historical predicted meteorological parameters and contemporaneous measured power data were used to learn physical coherence of wind speed and wind power output . Alexiadis, M.C. et al. [20] has illustrated a technique for forecasting two-hour-ahead wind speed and power based on cross correlation at neighboring sites. A methodology synthesizing both ANN technology and the linear regression are introduced in reference [21] by Wang, X. Reference [22] utilized the 4-8-1 neural network to estimate wind power. The four inputs include

measured data for wind velocities and directions from two meteorological towers. A method for establishing wind speed correlation between neighboring stations was presented in reference [23]. Reference [24] deals with the 72 hour ahead forecasting for wind speed and power based on meteorological information. M.S. Roulston et al.focuses on 1 10 day ahead prediction for wind speed. The authors utilized the forecasting results from the Numerical Weather Prediction (NWP) computer model run by the European Centre for Medium Range Weather Forecasting (ECMWF) [25]. Reference [26] developed a methodology that used a Bayesian framework to model the wind speed time series as an autoregressive process, where the Markov Chain Monte Carlo (MCMC) simulation is used to estimate the model parameters. EI-Fouly has presented one-day ahead prediction of wind speed using annual and seasonal trends [27]. Reference [27] presents a novel technique for one hour ahead wind speed forecasting based on the Grey model GM (1,1). Pinson, P. et al. [28] presented a wind forecasting system that uses on-line Supervisory Control and Data Aquisition (SCADA) system measurements and NWP as inputs to predict wind power. These forecasts are updated every hour based on the most recent wind power measurements. Recently a probabilistic neural network model was used to predict the daily load and Photovoltaic power [29]. Hao Quan et al. have implemented NN based method for the construction of Prediction Interval (PIs) [30]. Various algorithms for PV power prediction were proposed. Elminir et al. have proposed Multiple linear regression model to study the solar power output characteristics, combining with weather data and solar radiation data [31]. However, this method required large amount of data samples, and the fitting results were sensitive to pathological data. Other method based on Markov chain suggested by Y. Li [32] also relied on a large number of raw data, but it has shown higher accuracy. Furthermore, there are other machine learning algorithms such as kNN regression algorithms, the K-nearest neighbor technology has been validated to be a good way for future PV power prediction [33]. SVM was also applied to predict Photovoltaic (PV) power outputs [34]. Researchers also have combined SVM algorithms with other regression methods, so as to get more accurate estimations for short term PV forecasting [35]. PV forecasting based on artificial neural network (ANN) method was proposed in [36]. Recently, some improved algorithms have been developed on BP network to enhance better convergence [37], [38].

# 3 Research Gap

A number of reference models have been introduced as bench- mark models. These models may be used testing of the accuracy of new approaches to wind or solar power forecasting. Development activities are on-going in reducing the forecasting error in wind and solar power forecasting. With more accurate forecasting integration of large amounts of renewable power into power system can be achieved. Accurate forecasting tools reduce the financial risk and lead to improved scheduling and unit commitment plans. The statistical forecasting approaches, such as conventional statistical approaches, ANN, and ANNFuzzy, use large amounts of historical data as input. These approaches are mostly aimed at very short-term and short-term forecasting. ANN is able to model complex non-linear relationships and extract the dependence between the inputs and outputs through learning and training. Fuzzy logic outperforms others when dealing with reasoning problems, while learning and training abilities are mediocre. The merging of the ANN approach with the Fuzzy logic, creating the ANNFuzzy approach, provides excellent performance. It is difficult to say which model is the best because different models perform differently in different situations. The combination approach is able to not only improve the forecast accuracy, but also reduces the risk from extreme events. The general forecasting accuracy is then considered along with the level of forecasting errors that can be expected depending on the forecast time horizon, location complexity, seasonal variability, and weather conditions. The forecasting accuracy goes down with increasing forecast time horizon, terrain complexity, and unstable weather regimes. The reviewed renewable generation forecasting approaches provide a foundation for future research. Future work to be considered includes the following:

- Further improvements in both physical and statistical forecasting approaches and developing improved models from the combination of different forecasting approaches i.e. hybrid approaches can be expected to further reduce forecasting errors.

- Forecasting the aggregated renewable power on a regional basis would be useful for management of total renewable power production. It would also be useful to detect extreme events so that market operators can manage trading as wind/solar power ramps up and down.

- Additional use of online wind speed, solar irradiation measurement data has the potential for improved forecasts, especially for very short-term and short-term wind/solar power forecasting.

# 4 Objectives of Research

Almost all the countries are adopting deregulated industry structure for better utilization of the resources and for providing choice and quality service to the consumers at economical prices resulting in transparent price discovery. In the present day power systems, a lot of researchers and academicians are engaged in the activity of developing tools, models and algorithms for renewable power forecasting and is one of the major research fields in electrical engineering. Forecasting of renewable power, electric loads have become a major issue in power systems. The uncertainty associated with wind and solar power originates from uncertainties in weather conditions.

The objectives of the research will be

⇒ Brief literature review of intelligent energy management strategies for maximum utilization of renewable energy sources considering load demand, availability of renewable energy sources and state of charge of battery.

⇒ Developing different forecasting models for renewable generation and demand forecasting using physical forecasting approach, statistical forecasting approach or hybrid forecasting methods.

⇒ Carry out performance analysis of these forecasting methods against different environmental factors.

⇒ To simulate the proposed models using the tools in Matlab/ Simulink environment and carry out comparison among proposed forecasting models.

⇒ To develop decision making system for the battery scheduling process which schedule the battery with the rate of charge and discharge.

# 5 Methodology to be adopted

The aim of this Ph. D. work is to develop different forecasting methods like Statistical forecasting methods, Artificial Neural network or hybrid methods for renewable power generation and demand forecasting. These forecasting methodologies can be described briefly as follows:

## Wind Power Prediction

Wind power forecasting plays a key role in dealing with security, stability and economic operations of power systems. A high accuracy forecasting result can not only reduce the need for additional balancing energy and reserve power to integrate wind power, but also effectively reduce the impact of wind farms on the grid. Also an accurate wind power forecasting result provides favorable conditions for wind power bidding in the market, ensuring more competitive market trading as wind power ramps up and down the grid [39]. Existing wind farm power output forecasting methods can be divided into two kinds: physical model and statistical method. The physical model is based on physical modeling of wind farm location, all weather forecast data, geographical features of the wind farm should be taken as input digital [40]. This method is more suitable for long-term wind power forecasting. Statistical methods are based on historical data of wind power output, wind speed, wind direction, temperature and pressure and other digital weather forecast (NWP) data [41]. The models include spatial correlation method [20], spatial smoothing method, time series [42], [43], Kalman filtering method, the gray prediction method, etc. It can also be nonlinear models, such as artificial neural networks, wavelet analysis [44], support vector machine (SVM) regression method [45], fuzzy logic [46] and so on. Then the future wind farm power output is forecast by imputing the numerical weather prediction data and other information into the models. These kinds of methods are suitable for short-term wind power forecasting, which are important for the grid dispatching department. After study of different methods of short term and long term forecasting of wind power output, it was concluded that error will increases with increase in time scale. In order to improve the accuracy of the forecasting in different time scales, considering the wind speed characteristics this Ph. D. work will focus on establishing different hybrid forecasting models based on different algorithms for different time scales.

## Solar Power Output Prediction

To ensure reliable operation and economic dispatch of modern power systems, generation schedules are usually planned for real-time, one-day-ahead, weekly, monthly, and yearly power system operations. Therefore, it is essential to predict power system load curves and generation outputs of renewable power plants, such as wind power plants and solar photovoltaic (PV) power stations. As it is well-known that the outputs of solar PV power stations

have high variations subject to different weather conditions, research on PV power forecasting has become a great concern for power engineers in recent years. Various PV power output prediction algorithms have been proposed up to present. Multiple linear regression [47] was used to study the solar power output characteristics, combining with weather data and solar radiation data. However, this method required large amount of data samples, and the fitting results were sensitive to pathological data. Another method based on Markov chain [48], [49] also relied on a large number of raw data, but it has shown higher accuracy even if some weather data are omitted. Furthermore, there are other machine learning algorithms such as kNN regression algorithms, the K-nearest neighbor technology has been validated to be a good way for future PV power prediction [50]. Support vector machine (SVM) was also applied to predict PV power outputs [51]. However, SVM algorithms were originally proposed for classification problems, as for nonlinear regression problems such as PV power forecasting, it is not easy to choose suitable kernel functions and increase training speed during its quadratic programming process. Researchers also have combined SVM algorithms with other regression methods, so as to get more accurate estimations for short term PV forecasting [35]. One effective method for PV forecasting is the artificial neural network (ANN) method [52]. Among ANN-related methods, back propagation (BP) neural network has been more widely used because of its excellent nonlinear mapping function, especially suitable for solving complex regression problems. BP neural network has the advantages of complex nonlinear systems simulation ability, good approximation performance, strong learning ability, and large fault data tolerance. However, it also has some inherent defects, such as slow convergence rate, easy to fall into local minimum value so as not be able to get the global optimal solution. Recently, some improved algorithms have been developed on BP network to enhance better convergence [53], [54]. Solar power forecasting using hybrid model for improving the accuracy will be the area of research for the Ph.D. work.

## Load or Demand forecasting

Short term load forecasting can be useful for proper maintenance schedule and coordination of generation units. Moreover midterm and long term electrical load predictions can be applied for both future transmission and generation expansion planning. Time series-based methods like Auto Regressive Moving Average (ARMA) model and Auto Regressive Integrated Moving Average (ARIMA) model are very popular methods for load prediction. It uses the previous load data for prediction of next hours loads [55]. But future electri-

cal load are complicated and nonlinear functions of previous load and temperature data. Hence, some time series-based methods cannot yield precise prediction accuracy. Intelligent tools that are able to learn the relation between input and output vectors have been used in many researches for detection of electrical consumption load patterns. Feed Forward Artificial Neural Networks (FFANN) [56], Fuzzy Neural Network (FNN) [57], Support Vector Machines (SVMs) [58], [59] and Expert Systems (ES) [60] have been applied in the load forecasting area. Adaptive neural fuzzy inference system (ANFIS) based methods need complicated fuzzy rules to give acceptable prediction accuracy. ANN also suffers from two major drawbacks: first, the learning process is a very time-consuming task, and second, there is no exact rule for setting the parameters of NNs. Since electrical load consumption signals are non-stationary, signal analyzer tools can be applied for time series analysis. Some of these tools like Empirical Mode Decomposition (EMD) [61] analyze signals only in time domain and some of them like Wavelet Transform (WT) [62] analyze signals in both time and frequency [63], [64]. In some combined algorithms [65], [66], heuristic search algorithms have been applied for improvement of classifier operation by precise setting of adjustable parameters. From literature review, it is seen that since the value of all data is not the same, it is necessary to apply a feature selection method for elimination of less important features. This task improves the generalization capability of learning machine, and reduces both learning time and required memory for saving of data. Moreover, using two separate structures for prediction of weekdays and weekends as well as discriminative indices for different days can yield better prediction accuracy as compared to methods which uses a single predictor structure. This Ph. D. work aims in using Wavelet Transform for decomposition of electrical load signal into two levels. The obtained decomposed signals as well as temperature data create the training input matrices. SVM will be used as the predictor for learning of patterns of training matrix.

## Battery Scheduling

The energy management strategy deals with the battery scheduling process. The efficient battery scheduling is to be considered for actual demand, availability of renewable energy sources and electricity price. The battery scheduling is the part of decision making process. The way to solve this problem is to design a expert system which can decide , referring to actual and forecasted data, whether the battery should be charged or discharged. In this Ph. D. work it is decided to use fuzzy-logic based expert system for battery scheduling process.

# 6 Year-wise Plan of Research

| Sr. No. | Work to be done | Required Time |
|---|---|---|
| 1 | Literature study time | 3 Months |
| 2 | Market Data collection time | 6 Months |
| 3 | Data Tabulation and Data Analysis | 3 Months |
| 4 | Development of different models for Wind and Solar Power Generation and Load forecasting | 1 year |
| 5 | Validation of different models and comparison | 6 Months |
| 6 | Publication of results in the form of research papers | 6 Months |

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# References


[1] A. Tascikaraoglu, A. Boynuegri, and M. Uzunoglu, "A demand side management strategy based on forecasting of residential renewable sources: A smart home system in turkey," *Energy and Buildings*, vol. 80, pp. 309 – 320, 2014.

[2] J. Pascual, J. Barricarte, P. Sanchis, and L. Marroyo, "Energy management strategy for a renewable-based residential microgrid with generation and demand forecasting," *Applied Energy*, vol. 158, pp. 12 – 25, 2015.

[3] H.-T. Yang and C.-M. Huang, "A new short-term load forecasting approach using self-organizing fuzzy armax models," *IEEE Transactions on Power Systems*, vol. 13, no. 1, pp. 217–225, Feb 1998.

[4] A. Demiroren and G. Ceylan, "Middle anatolian region short-term load forecasting using artificial neural networks," *Electric Power Components and Systems*, vol. 34, no. 6, pp. 707–724, 2006.

[5] M. Lpez, S. Valero, C. Senabre, J. Aparicio, and A. Gabaldon, "Application of {SOM} neural networks to short-term load forecasting: The spanish electricity market case study," *Electric Power Systems Research*, vol. 91, pp. 18 – 27, 2012.

[6] A. G. Bakirtzis, J. B. Theocharis, S. J. Kiartzis, and K. J. Satsios, "Short term load forecasting using fuzzy neural networks," *IEEE Transactions on Power Systems*, vol. 10, no. 3, pp. 1518–1524, Aug 1995.

[7] D. Srinivasan, C. S. Chang, and A. C. Liew, "Demand forecasting using fuzzy neural computation, with special emphasis on weekend and public holiday forecasting," *IEEE Transactions on Power Systems*, vol. 10, no. 4, pp. 1897–1903, Nov 1995.

[8] S. C. Pandian, K. Duraiswamy, C. C. A. Rajan, and N. Kanagaraj, "Fuzzy approach for short term load forecasting," *Electric Power Systems Research*, vol. 76, no. 67, pp. 541 – 548, 2006.

[9] B.-J. Chen, M.-W. Chang, and C.-J. lin, "Load forecasting using support vector machines: a study on eunite competition 2001," *IEEE Transactions on Power Systems*, vol. 19, no. 4, pp. 1821–1830, Nov 2004.

[10] H. shan Wu and S. Zhang, "Power load forecasting with least squares support vector machines and chaos theory," in *2005 International Conference on Neural Networks and Brain*, vol. 2, Oct 2005, pp. 1020–1024.

[11] S. Rahman and R. Bhatnagar, "An expert system based algorithm for short term load forecast," *IEEE Transactions on Power Systems*, vol. 3, no. 2, pp. 392–399, May 1988.

[12] R.-A. Hooshmand, H. Amooshahi, and M. Parastegari, "A hybrid intelligent algorithm based short-term load forecasting approach," *International Journal of Electrical Power and Energy Systems*, vol. 45, no. 1, pp. 313 – 324, 2013.

[13] R. Piwko, D. Osborn, R. Gramlich, G. Jordan, D. Hawkins, and K. Porter, "Wind energy delivery issues [transmission planning and competitive electricity market operation]," *IEEE Power and Energy Magazine*, vol. 3, no. 6, pp. 47–56, Nov 2005.

[14] E. Nogaret, G. Stavrakakis, G. Kariniotakis, M. Papadopoulos, N. Hatziargyriou, A. Androutsos, S. Papathanassiou, J. Lopes, J. Halliday, G. Dutton, J. Gatopoulos, and V. Karagounis, "An advanced control system for the optimal operation and management of medium size power systems with a large penetration from renewable power sources," *Renewable Energy*, vol. 12, no. 2, pp. 137 – 149, 1997.

[15] J. Torres, A. Garca, M. D. Blas, and A. D. Francisco, "Forecast of hourly average wind speed with {ARMA} models in navarre (spain)," *Solar Energy*, vol. 79, no. 1, pp. 65 – 77, 2005.

[16] G. N. Kariniotakis, G. S. Stavrakakis, and E. F. Nogaret, "Wind power forecasting using advanced neural networks models," *IEEE Transactions on Energy Conversion*, vol. 11, no. 4, pp. 762–767, Dec 1996.

[17] C. W. Potter and M. Negnevitsky, "Very short-term wind forecasting for tasmanian power generation," *IEEE Transactions on Power Systems*, vol. 21, no. 2, pp. 965–972, May 2006.

[18] P. M. Fonte and J. C. Quadrado, "Ann approach to wecs power forecast," in *2005 IEEE Conference on Emerging Technologies and Factory Automation*, vol. 1, Sept 2005, pp. 4 pp.–1072.

[19] K. Rohrig and B. Lange, "Application of wind power prediction tools for power system operations," in *2006 IEEE Power Engineering Society General Meeting*, 2006, pp. 5 pp.–.

[20] M. C. Alexiadis, P. S. Dokopoulos, and H. S. Sahsamanoglou, "Wind speed and power forecasting based on spatial correlation models," *IEEE Transactions on Energy Conversion*, vol. 14, no. 3, pp. 836–842, Sep 1999.

[21] X. Wang, G. Sideratos, N. Hatziargyriou, and L. H. Tsoukalas, "Wind speed forecasting for power system operational planning," in *Probabilistic Methods Applied to Power Systems, 2004 International Conference on*, Sept 2004, pp. 470–474.

[22] S. Li, D. C. Wunsch, E. A. O'Hair, and M. G. Giesselmann, "Using neural networks to estimate wind turbine power generation," *IEEE Transactions on Energy Conversion*, vol. 16, no. 3, pp. 276–282, Sep 2001.

[23] D. A. Bechrakis and P. D. Sparis, "Correlation of wind speed between neighboring measuring stations," *IEEE Transactions on Energy Conversion*, vol. 19, no. 2, pp. 400–406, June 2004.

[24] T. G. Barbounis, J. B. Theocharis, M. C. Alexiadis, and P. S. Dokopoulos, "Long-term wind speed and power forecasting using local recurrent neural network models," *IEEE Transactions on Energy Conversion*, vol. 21, no. 1, pp. 273–284, March 2006.

[25] M. Roulston, D. Kaplan, J. Hardenberg, and L. Smith, "Using medium-range weather foercasts to improve the value of wind energy production," *Renewable Energy*, vol. 28, no. 4, pp. 585 – 602, 2003.

[26] M. S. Miranda and R. W. Dunn, "One-hour-ahead wind speed prediction using a bayesian methodology," in *2006 IEEE Power Engineering Society General Meeting*, 2006, pp. 6 pp.–.

[27] T. H. M. El-Fouly, E. F. El-Saadany, and M. M. A. Salama, "One day ahead prediction of wind speed using annual trends," in *2006 IEEE Power Engineering Society General Meeting*, 2006, pp. 7 pp.–.

[28] P. Pinson and G. N. Kariniotakis, "Wind power forecasting using fuzzy neural networks enhanced with on-line prediction risk assessment," in *Power Tech Conference Proceedings, 2003 IEEE Bologna*, vol. 2, June 2003, pp. 8 pp. Vol.2–.

[29] B. R. Ke, T. T. Ku, Y. L. Ke, C. Y. Chuang, and H. Z. Chen, "Sizing the battery energy storage system on a university campus with prediction of load and photovoltaic generation," *IEEE Transactions on Industry Applications*, vol. 52, no. 2, pp. 1136–1147, March 2016.

[30] H. Quan, D. Srinivasan, and A. Khosravi, "Short-term load and wind power forecasting using neural network-based prediction intervals," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 25, no. 2, pp. 303–315, Feb 2014.

[31] H. K. Elminir, Y. A. Azzam, and F. I. Younes, "Prediction of hourly and daily diffuse fraction using neural network, as compared to linear regression models," *Energy*, vol. 32, no. 8, pp. 1513 – 1523, 2007.

[32] Y. Z. Li and J. C. Niu, "Forecast of power generation for grid-connected photovoltaic system based on markov chain," in *2009 Asia-Pacific Power and Energy Engineering Conference*, March 2009, pp. 1–4.

[33] B. Saghafian, S. Anvari, and S. Morid, "Effect of southern oscillation index and spatially distributed climate data on improving the accuracy of artificial neural network, adaptive neuro-fuzzy inference system and k-nearest neighbour streamflow forecasting models," *Expert Systems*, vol. 30, no. 4, pp. 367–380, 2013.

[34] J. Shi, W. J. Lee, Y. Liu, Y. Yang, and P. Wang, "Forecasting power output of photovoltaic systems based on weather classification and support vector machines," *IEEE Transactions on Industry Applications*, vol. 48, no. 3, pp. 1064–1069, May 2012.

[35] M. Bouzerdoum, A. Mellit, and A. M. Pavan, "A hybrid model (sarimasvm) for short-term power forecasting of a small-scale grid-connected photovoltaic plant," *Solar Energy*, vol. 98, Part C, pp. 226 – 235, 2013.

[36] W. Fei, M. Zengqiang, S. Shi, and Z. Chengcheng, "A practical model for single-step power prediction of grid-connected pv plant using artificial neural network," in *Innovative Smart Grid Technologies Asia (ISGT), 2011 IEEE PES*, Nov 2011, pp. 1–4.

[37] F. Bizzarri, M. Bongiorno, A. Brambilla, G. Gruosso, and G. S. Gajani, "Model of photovoltaic power plants for performance analysis and production forecast," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 2, pp. 278–285, April 2013.

[38] C. Chen, S. Duan, T. Cai, and B. Liu, "Online 24-h solar power forecasting based on weather type classification using artificial neural network," *Solar Energy*, vol. 85, no. 11, pp. 2856 – 2870, 2011.

[39] J. Jung and R. P. Broadwater, "Current status and future advances for wind speed and power forecasting," *Renewable and Sustainable Energy Reviews*, vol. 31, pp. 762 – 777, 2014.

[40] M. Lei, L. Shiyan, J. Chuanwen, L. Hongling, and Z. Yan, "A review on the forecasting of wind speed and generated power," *Renewable and Sustainable Energy Reviews*, vol. 13, no. 4, pp. 915 – 920, 2009.

[41] G. Sideratos and N. D. Hatziargyriou, "An advanced statistical method for wind power forecasting," *IEEE Transactions on Power Systems*, vol. 22, no. 1, pp. 258–265, Feb 2007.

[42] M. G. D. Giorgi, A. Ficarella, and M. Tarantino, "Assessment of the benefits of numerical weather predictions in wind power forecasting based on statistical methods," *Energy*, vol. 36, no. 7, pp. 3968 – 3978, 2011.

[43] J. W. Taylor, P. E. McSharry, and R. Buizza, "Wind power density forecasting using ensemble predictions and time series models," *IEEE Transactions on Energy Conversion*, vol. 24, no. 3, pp. 775–782, Sept 2009.

[44] J. Catalo, H. Pousinho, and V. Mendes, "Short-term wind power forecasting in portugal by neural networks and wavelet transform," *Renewable Energy*, vol. 36, no. 4, pp. 1245 – 1251, 2011.

[45] Z. Liang, J. Liang, C. Wang, X. Dong, and X. Miao, "Short-term wind power combined forecasting based on error forecast correction," *Energy Conversion and Management*, vol. 119, pp. 215 – 226, 2016.

[46] H. M. I. Pousinho, V. M. F. Mendes, and J. P. S. Catalo, "Application of adaptive neuro-fuzzy inference for wind power short-term forecasting," *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 6, no. 6, pp. 571–576, 2011.

[47] S. I. Sulaiman, T. K. A. Rahman, I. Musirin, and S. Shaari, "Artificial neural network versus linear regression for predicting grid-connected photovoltaic system output," in

*Cyber Technology in Automation, Control, and Intelligent Systems (CYBER), 2012 IEEE International Conference on*, May 2012, pp. 170–174.

[48] Y. z. Li, R. Luan, and J. c. Niu, "Forecast of power generation for grid-connected photovoltaic system based on grey model and markov chain," in *2008 3rd IEEE Conference on Industrial Electronics and Applications*, June 2008, pp. 1729–1733.

[49] J. Song, V. Krishnamurthy, A. Kwasinski, and R. Sharma, "Development of a markov-chain-based energy storage model for power supply availability assessment of photovoltaic generation plants," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 2, pp. 491–500, April 2013.

[50] H. Long, Z. Zhang, and Y. Su, "Analysis of daily solar power prediction with data-driven approaches," *Applied Energy*, vol. 126, pp. 29 – 37, 2014.

[51] J. Shi, W.-J. Lee, Y. Liu, Y. Yang, and P. Wang, "Forecasting power output of photovoltaic system based on weather classification and support vector machine," in *Industry Applications Society Annual Meeting (IAS), 2011 IEEE*, Oct 2011, pp. 1–6.

[52] T.-C. Yu and H.-T. Chang, "The forecast of the electrical energy generated by photovoltaic systems using neural network method," in *Electric Information and Control Engineering (ICEICE), 2011 International Conference on*, April 2011, pp. 2758–2761.

[53] E. zgi, A. ztopal, B. Yerli, M. K. Kaymak, and A. D. ahin, "Shortmid-term solar power prediction by using artificial neural networks," *Solar Energy*, vol. 86, no. 2, pp. 725 – 733, 2012.

[54] A. Yona, T. Senjyu, A. Y. Saber, T. Funabashi, H. Sekine, and C. H. Kim, "Application of neural network to 24-hour-ahead generating power forecasting for pv system," in *Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE*, July 2008, pp. 1–6.

[55] C.-M. Lee and C.-N. Ko, "Short-term load forecasting using lifting scheme and {ARIMA} models," *Expert Systems with Applications*, vol. 38, no. 5, pp. 5902 – 5911, 2011.

[56] H. ze Li, S. Guo, C. jie Li, and J. qi Sun, "A hybrid annual power load forecasting model based on generalized regression neural network with fruit fly optimization algorithm," *Knowledge-Based Systems*, vol. 37, pp. 378 – 387, 2013.

[57] D. Ranaweera, N. Hubele, and G. Karady, "Fuzzy logic for short term load forecasting," *International Journal of Electrical Power and Energy Systems*, vol. 18, no. 4, pp. 215 – 222, 1996.

[58] C.-N. Ko and C.-M. Lee, "Short-term load forecasting using {SVR} (support vector regression)-based radial basis function neural network with dual extended kalman filter," *Energy*, vol. 49, pp. 413 – 422, 2013.

[59] Q. Wu, "Power load forecasts based on hybrid pso with gaussian and adaptive mutation and wv-svm," *Expert Syst. Appl.*, vol. 37, no. 1, pp. 194–201, Jan. 2010.

[60] K.-L. Ho, Y.-Y. Hsu, C.-F. Chen, T.-E. Lee, C.-C. Liang, T.-S. Lai, and K.-K. Chen, "Short term load forecasting of taiwan power system using a knowledge-based expert system," *IEEE Transactions on Power Systems*, vol. 5, no. 4, pp. 1214–1221, Nov 1990.

[61] Z. Zhu, Y. Sun, and H. Li, "Hybrid of emd and svms for short-term load forecasting," in *2007 IEEE International Conference on Control and Automation*, May 2007, pp. 1044–1047.

[62] S. G. Mallat, "A theory for multiresolution signal decomposition: the wavelet representation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 11, no. 7, pp. 674–693, July 1989.

[63] Z. A. Bashir and M. E. El-Hawary, "Applying wavelets to short-term load forecasting using pso-based neural networks," *IEEE Transactions on Power Systems*, vol. 24, no. 1, pp. 20–27, Feb 2009.

[64] Y. Chen, P. B. Luh, C. Guan, Y. Zhao, L. D. Michel, M. A. Coolbeth, P. B. Friedland, and S. J. Rourke, "Short-term load forecasting: Similar day-based wavelet neural networks," *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 322–330, Feb 2010.

[65] Q. Wu, "Hybrid model based on wavelet support vector machine and modified genetic algorithm penalizing gaussian noises for power load forecasts," *Expert Systems with Applications*, vol. 38, no. 1, pp. 379 – 385, 2011.

[66] M. Ulagammai, P. Venkatesh, P. Kannan, and N. P. Padhy, "Application of bacterial foraging technique trained artificial and wavelet neural networks in load forecasting," *Neurocomputing*, vol. 70, no. 1618, pp. 2659 – 2667, 2007.